How does P2P lending platform reputation affect lenders' decision in China?

Xiaokun, Shi[1]; Junjie Wu[2 *]; Jane Hollingsworth[3]

[1]School of Finance, Zhejiang Gongshang University, China

[2, 3] Leeds Business School, Leeds Beckett University, UK

Abstract

Purpose – This paper examines how the impact of Chinese P2P platform reputation directly and indirectly (mediate effect) affects investors' (lenders) investment choices.

Design/methodology/approach – Using data collected from 478 P2P platforms, this paper calculates *Platform Reputation* via a beta function after establishing the *Reputation* mechanism by Game Analysis. This is followed by testing both the direct effect of platform reputation on investors' investment choices (proxying by transaction volume) and the indirect effect through credit enhancing information using three regression models (Median regression, OLS regression, and random effect OLS regression). A robustness test by adding instrument variables is conducted to confirm the findings from the main regressions.

Findings – In China, P2P lending platform reputations have played both a direct and indirect (through credit enhancing information) roles on investors' investment choices.

Originality/value – This paper expands the boundary of P2P online lending research by not only examining the direct, but importantly, the indirect effects of platform reputations.

Key words: Reputation mechanism, Moral hazard, P2P lending, Online platform, China

Paper type: Research paper

1. Introduction

Following the first peer-to-peer (P2P) online platform (Zopa) in the world launched in the UK in 2005, the first Chinese online P2P lending platform (CreditEase) was established in 2006. The P2P online lending market in China has dramatically surged in recent years. For example: the number of P2P lending platforms in 2010 was only 15; 148 in 2012; 523 in 2013; 900 in 2014 (Wei, 2015); and by the end of June 2018, the numbers reached 1,863. According to The International Organization of Securities Commission (IOSCO), China is the third country after the US and the UK in terms of P2P transaction value (Mo, 2014). The driving forces of the sharp rise in P2P platforms include the significant increase in the numbers of rich people in China (especially middle-class young generation), the government's tightening monetary policy in 2007, the bear stock and property market since 2011, and the development of new internet technology. The popularity of the online lending market is because P2P platforms can facilitate bank functions by acting as an intermediary channel effectively connecting between many small-scale lenders who have spare money to invest, hoping for a better return than the interest they would achieve in a bank. In fact, these small-scale borrowers (mainly small and micro enterprises and individuals) find it difficult to obtain bank loans without collateral (Yum et al., 2012).

Simultaneously, significant numbers of these platforms in China are unhealthy and problematic. According to one of the main P2P portals (P2Peye), as of December 2017, the problematic platforms in China reached 50.69%, within which 54.2% were platforms that the owners of platforms illegally ran away with or hid cash ('Paolu' in Chinese); as a consequence, these platforms were unable to maintain normal operations. For example, in July 2018, 218 problem platforms collapsed, causing panic among investors and the public. Some victims demonstrated on the street for the right to get their money back, and in some extreme cases, victims even committed suicide. The recent severe turmoil of P2P online leading was defined as a 'financial explosion' ('Baolei' in Chinese, meaning 'bomb exploded') which spotlighted a moral hazard issue of P2P platforms.

The concept of moral hazard was widely used by British insurance companies in the late 19th century representing fraud or immoral behaviour. In his book "The Return of Depression Economics and the Crisis of 2008," the economist and Nobel Prize winner Paul Krugman described moral hazard as "*…any situation in which one person makes the decision about how much risk to take, while someone else bears the cost if things go badly*" (Krugman, 2009, p. 63). In other words, moral hazard involves a contract affecting the behaviour of two parties (principal-agent model) under the circumstance of information asymmetry: the agent (holding better information) has incentives to change their behaviour while the subsequent risk is at the expense of the principal (holding less information). Examples of moral hazard are broadly observed in the fields of insurance, consumer behaviour, and finance. In the context of P2P online lending, we propose moral hazard to be, due to information asymmetry, online lending platforms deliberately hiding some information (e.g. the borrowers' true credit information) or taking risky behaviour in order to maximise its own profits/commissions at the cost of the investors (the lenders).

Figure 1 shows a disproportionate development between the numbers of new and hazardous platforms during 2010 – 2017 in China.

Insert Figure 1 here

The emergence of significant moral hazard issues in China along with the rapid growth of P2P online lending platforms can be analysed from the differences in institutional, regulatory, and industrial environments, compared to other developed countries such as the UK and the US.

With regards to the institutional environment in the UK and the US, the development of P2P online lending has been integrated and compatible with a highly developed financial system, for example, SMEs and individuals freely have access to the lending facilities provided by commercial banks, building societies and P2P lending platforms depending on their needs and preference. In contrast, China has long been dominated by state-owned commercial banks which provide their loans mainly to large and medium-sized state-owned enterprises while privately small and micro enterprises, and farmers (who are the main borrowers on P2P platforms) are discriminated. On the other hand, stock and property markets have fluctuated for a long period of time and many individual investors (the main providers of funds to P2P platforms) have to seek investment returns from P2P platforms, even having knowledge that this may be of high risk (Chen, 2016).

In terms of the regulatory environment, both the UK and the US have well-established online lending regulations including market access threshold, registration and quality of information disclosed. For instance, all P2P online lending platforms are regulated by the Securities and Exchange Commission (SEC) in the US and by the Financial Conduct Authority (FCA) in the UK. The relevant regulatory frameworks are designed to achieve the primary purposes of protecting consumers, promoting fair and effective competition within the industry, ensuring platforms provide transparent and nonmisleading information to the users, ensuring P2P platforms maintain sustainable development, and having contingency arrangements in the event of platform failure. Whilst in China, in the initial stages (2006-2012) and during rapid development (2013-2015) of the P2P lending market, there were no formal industry regulations (i.e. no market access threshold, no registration policy and no information disclosure requirements) and all written documents were at the level of "Opinions and Suggestions" to the sector and heavily relied on the sector's self-discipline (Chen, 2016). This legal loophole was seized by some owners of P2P platforms who used the platforms as illegal fund-raising tools and who would then disappear with investors' money. As such, the absence of a regulatory system caused chaotic and moral hazard problems. It wasn't until 2016 that the Chinese government began to pay attention to the regulations of the online lending market; however, the Chinese framework still requires substantial improvement.

Regarding the industry environment, we refer to the credit rating of borrowers and platform risk control. In the UK, a sound credit database collected by national credit bureaus that provides a unified credit rating for individuals (including car loans, mortgages, credit cards and default payment records) is available to use by P2P online lending platforms. A similar system is operated in the US (e.g. FICO score). However, in China there is no such national unified personal credit rating system. The lack of a unified and credible database for online credit ratings results in most P2P online lending platforms only disclosing credit information provided by the borrowers; some responsible platforms may carry out additional checks for the authenticity and reliability of this information (Chen, 2016). In other words, P2P platforms in China bear much higher default risks by borrowers than their counterparts in the UK and the US, which highlights the importance of *platform reputation* (the issue of our paper's focus) as it can reduce uncertainty in this new industry and mitigate the moral hazard caused.

Platform reputation refers to P2P participants' (particularly lenders) perception of the platform's institutional mechanism that can effectively facilitate lending success and protect their interest. Extant studies are concentrated on issues such as the operation mode of online P2P lending, the impact of 'hard' information (e.g. personal information) and 'soft' information (e.g. participants' comments on social media) on lending outcomes (Chen and Han, 2012). Online customer reviews/feedback can affect the reputation of online platforms, for example, eBay, Taobao, and EachNet indicate that reputation built on customer feedback can effectively affect platform behaviour in service improvement (Howcroft et al., 2012; Wu and Li, 2009; Cai et al., 2014; Li et al., 2016). However, issues such as how platform reputation affect lenders' investment decision and in what ways, are largely omitted.

To address this gap, this paper has examined the direct and indirect (mediating) effect of P2P platform reputation on investors lending decision using data collected from 478 P2P platforms listed on the most influential P2P lending portals holding by third parties (WDZJ-网贷之家 and P2Peye-网贷天眼). Firstly, platform *Reputation* was calculated based on investors' evaluations using beta function. Secondly, using median regression, OLS regression and random effect OLS regression respectively, we tested the direct effect of platform reputation on investors' investment choices (using lending transaction volume as the proxy) and the indirect effect through platform credit enhancing information (i.e. platform registered capital, platform location, types of platforms, etc.). Thirdly, we ran further tests by adding some instrument variables (i.e. CEO's education background, membership of professional associations) to confirm the direct and indirect factors, and finally, we ran a robustness test by replacing transaction volume using the duration of platforms to conclude the regression results.

The structure of the paper is arranged as follows: section 2 builds the *platform reputation* mechanism using Game Analysis; section 3 develops hypotheses for testing; section 4 explains data collection, variables, measurements, and analytical models; section 5 presents all empirical findings; and finally, section 6 concludes the findings and discusses the contributions, implications, and limitations.

2. The Market for Lemons' theory, Signal Theory and *Reputation* mechanism in Game Analysis

Taking second-hand cars as an example of the problem of quality uncertainty when information held by buyers and sellers are asymmetric, Akerlof (1970) created the "Market for Lemons" theory. The theory suggests, some cars are "lemons" (in American slang, meaning defective used cars) and some are good quality cars. In the car selling market, buyers can never be told which cars are "lemons" and which are not, but sellers know them clearly. As such, buyers are only willing to pay a price representing an average quality car, and this (lower price to good quality cars) would consequently discourage the owners of good quality cars to sell their cars. Accordingly, buyers may risk ending up with a "lemon" (a defective car).

An effective way of solving the "Market for Lemons" problem is through signal transmission. According to Signal Theory (Spence, 1974), market signals are individual behaviours and characteristics (such as education level, reputation, and brand) that can be observed by other market participants which can convey information in the market. Spence argues that market participants can turn low-level signals into high-level signals by adding some costs. Taking the used car market as an example again, sellers with good quality cars can provide a warranty with their cars in order to provide a positive signal to potential buyers about the quality of their cars (Zhang, 2013). Of course, sellers with “lemons” will not be willing to provide such a warranty. Therefore, the warranty is provided as an effective market signal to convey and distinguish the different qualities of the used cars. In the process of repeated games, “warranty” can represent the “*reputation*” of good quality cars.

Similarly, in the P2P online lending market, lenders (investors) hold less information about borrowers than the platforms, but they can provide online ratings to record their satisfaction or dissatisfaction of the lending experience. In a repeated game, this rating can be thought as an effective signal to distinguish the different qualities of online lending platforms. In other words, investor rating on platforms can be used as a proxy of the platform *reputation.* In this section, we use Game Analysis to analyse and prove how the *reputation* of an online lending platform can be built and why it can be used as an effective signal to distinguish the qualities of online lending platforms.

Reputation mechanism

Assuming that investors are rationally seeking to maximise their utility, there are two types of platforms: low quality platforms (θ_1) and high-quality platforms (θ_2); θ_1=1, θ_2=2. Platform reputation (R) also has two types: low reputation platform (R_1) and high reputation platform (R_2); R_1=0 and R_2=1. Assuming that the cost function of platform reputation is $C(R, \theta)=1.5R/\theta$, it suggests that to build the same reputation level, the platforms with different levels of quality need to pay differing amounts of costs.

If an investor decides to invest on the platform based on its reputation level，the investment amount is $L(R)= \theta$, and when $R=R_1$, $L(R)=\theta_1$ and when $R=R_2$, $L(R)=\theta_2$. Assuming intermediary fees, commissions, and management charges are the main income sources of the online platforms, platforms that have better reputations should earn higher income because attracting more investors would result in greater transactions. That is, supposing the income function of the platform is: $I(R, \theta)=\theta$, the utility function of the platform is $U(R, L)=L-1.5R/ \theta$. That is to say, the greater the trading volume of the platform, the higher the utility of the platform. To improve its reputation, the platform would pay more costs, and thus the utility of the platform would be reduced. In order to simplify the analysis, it is assumed that under the conditions of complete competition, $L(R)=I(R, \theta)$, the competitive utility of the platform is 0.

In fact, borrowers and lenders do not know whether the quality of the platform is high or low, and investors only know the probability distribution of the platform type. Assuming the prior probability is the same to all platforms, i.e. $P(\theta_1)=P(\theta_2)=1/2$, in the absence of reputation information, investors make choice purely based on the prior probability. Suppose the expected future earnings of the platform is $E(I)$, and $E(I)=I(\theta_1)\ P(\theta_1) + I(\theta_2)\ P(\theta_2)$, that is $E(I) = (1 + 2) / 2 = 1.5$. The maximum expected income for high quality and low quality platforms is $I(\theta_2)=2$ and $I(\theta_1)=1$ respectively. As indicated by $I(\theta_2)< E(I)$ and $I(\theta_1)> E(I)$, it indicates that lower quality platforms receive more income and the higher quality platforms receive less income. According to the utility function U(R, L)= L-

$1.5R/\theta$, one can see that high quality platforms can reduce their effectiveness due to receiving less investment; while low quality platforms can increase their effectiveness due to higher investment scale; as such adverse selection problems occurred.

After adding reputation information, platforms have more choices of utility regardless of their quality.

For low-quality platforms, the utility choices under different reputations are:

If $\theta = \theta_1=1$， when $R=R_1=0$， $L(R)= \theta_1=1$， then $U (R_1, L) =L-1.5R/\theta =1$；

when $R=R_2=1$， $L(R)= \theta_2=2$， then $U (R_2, L) =L-1.5R/\theta =0.5$.

For high-quality platforms, the utility choices under different reputations are:

If $\theta = \theta_2=2$， when $R=R_1=0$， $L(R)= \theta_1=1$， then $U (R_1, L) =L-1.5R/\theta =1$；

when $R=R_2=1$， $L(R)= \theta_2=2$， then $U (R_2, L) =L-1.5R/\theta =1.25$.

It can be seen that for low quality platforms, $U(R_1, \theta_1)> U(R_2, \theta_1)$, which means low reputation would maximise the utility (a wise option); for high quality platforms, as $U(R_1, \theta_2)< U(R_2, \theta_2)$, it suggests continuously maintaining their high reputation would be the most effective choice. Theoretically, *Reputation* can distinguish platforms by qualities, and through platform reputational signal, investors can make their choices.

Behavioural choice of investors

According to the Bayesian rule, by having reputation information, investors can make investment choices based on the posteriori probability (P'(θ)) which is corrected prior probability after considering reputation information. Supposing the prior probability for all platforms is the same, that is, P (θ_1) =P (θ_2) =1/2, the probability for the platforms with high reputation and high quality is P ($R_2|\theta_2$), and the probability for the platforms with low reputation and low quality is P ($R_1|\theta_1$). The probability for platforms with low reputation and high quality platform is P ($R_1|\theta_2$), and the probability for the platforms with high reputation and low quality platform is P ($R_2|\theta_1$).

If investors receive information: the reputation for low quality platform is $R=R_1$, then according to the Bayesian rule, investors will get the posteriori probability P'(θ_1 |R_1) for the platforms with low quality to maintain their reputation as follows:

$$P'(\theta_1/R_1) = \frac{\mathrm{P}(R_1/\theta_1)\mathrm{P}(\theta_1)}{P(R_1)} = \frac{\mathrm{P}(R_1/\theta_1)\mathrm{P}(\theta_1)}{\mathrm{P}(R_1/\theta_2)\mathrm{P}(\theta_2) + \mathrm{P}(R_1/\theta_1)\mathrm{P}(\theta_1)},$$

$$\text{as } \mathrm{P}(\theta_1) = \mathrm{P}(\theta_2) = 0.5,$$

$$\text{then } P'(\theta_1/R_1) = \frac{\mathrm{P}(R_1/\theta_1)}{\mathrm{P}(R_1/\theta_2)+\mathrm{P}(R_1/\theta_1)}$$

For platforms with low reputation, their maintaining high quality probability P ($R_1|\theta_2$) is less than the low quality probability P ($R_1|\theta_1$); therefore P'($\theta_1|R_1$) > P (θ_1), (0.5), i.e. posterior probability is greater than the prior probability, thus on the basis of prior probability, investors would further revise prior probability and conclude the probability of these platforms in providing low quality services is greater than the prior probability. As a result, investors will reduce investment.

Similarly,

$$P'(\theta_2/R_2) = \frac{\mathrm{P}(R_2/\theta_2)\mathrm{P}(\theta_2)}{P(R_2)} = \frac{\mathrm{P}(R_2/\theta_2)\mathrm{P}(\theta_2)}{\mathrm{P}(R_2/\theta_1)\mathrm{P}(\theta_1) + \mathrm{P}(R_2/\theta_2)\mathrm{P}(\theta_2)} = \frac{\mathrm{P}(R_2/\theta_2)}{\mathrm{P}(R_2/\theta_1) + \mathrm{P}(R_2/\theta_2)}$$

For platforms with high reputation, $P(R_2|\theta_1)$ is less than $P(R_2|\theta_2)$, then $P'(\theta_2|R_2) > P(\theta_2)$ (0.5), posterior probability is greater than the prior probability, investors would conclude the probability of these platforms in providing high quality services is greater than the prior probability. Consequently, investors will increase investment.

The role of reputation mechanisms in mitigating moral hazard

Studies on reputation mechanisms are generally mature (Greif, 1993; Brown et al., 2000). According to the KMRW reputation model, reputation premium generated during a long-term repeated game will lead to improved cooperation between the participants, avoiding the occurrence of the prisoner's dilemma[1] (Kreps and Wilson, 1982; Shi et al., 2015).

Based on studies conducted by Xiao and Sheng (2003) and Greif (2004) on reputation mechanisms, assume that there are *n* online lending platforms and *N* potential investors, and each investor can only choose one lending platform and one lending project in each game. Lending platforms are chosen randomly. In such a case, the probability for lending platform "*P*" to be chosen by investor "*I*" is $1/n$, and each platform is expected to see N/n lending projects at most in each game. If an online lending

[1] A typical example in game theory that shows a paradox in decision analysis that two completely rational individuals may act in their own self-interests at the expense of the other participant which results no optimal outcome.

platform chooses to cheat an investor through concealing information, it can obtain short-term income *d*; if it chooses to disclose strictly selected information, it can obtain the income *c* ($d > c$). The discount factor is δ. If an investor is cheated because it cannot directly monitor the behaviour of the platform, it will spread the bad faith of the platform to *k-1* potential investors, and the value of *k-1* is determined by the speed and scope of information spreading. If the investor applies the trigger strategy, the investor and all other potential investors who receive the information will not invest on this platform in the future.

Only when the long-term income is greater than the short-term income, the *reputation mechanism* would motivate online lending platforms to disclose strictly selected information of borrowers, that is,

$$d - c \leq \frac{\delta}{1-\delta} \cdot \frac{kc}{n}$$

or

$$\frac{d-c}{c} \leq \frac{\delta}{1-\delta} \cdot \frac{k}{n} \qquad (1)$$

Whether inequality (1) can hold is determined by the value of $\frac{k}{n}$ in which *n* refers to the number of online lending platforms which will not change significantly due to the behavioural choice of a certain platform. The value of $\frac{k}{n}$ is mainly determined by *k*, which refers to the number of potential investors knowing the bad faith of the platform.

Platform reputation related information will become open and observable once credit scores of borrowers rated by investors and other lending-related information are publicly available (Wu, 2007; Dellarocas et al., 2008; Jolivet, 2016; Fan et al., 2016). Likewise, platform reputation based on investors' reviews can spread quickly in the case that these platforms have fraudulent behaviour. In such a case, the value of k in the equation (1) will be great enough, thus more potential investors can receive reputation information of the platform based on existing investors' reviews and walk away from investing in it. By repeating the process, the reputation mechanism can mitigate moral hazard in P2P lending.

3. Hypothesis development

From the discussions in the last section, we can see that information asymmetry (a typical example of "Market for Lemons") is a serious problem in the market. Due to differences in institutional, regulatory, and industrial environments, the information asymmetry in Chinese P2P lending is even more serious which has caused a great deal of uncertainty, suggesting the sector is under endogenous high risk which could lead to a serious consequence of fraudulent activities at some point.

Holmstrom (1984) proposed several remedies for mitigating asymmetric information and one of them is *reputation* – a kind of 'soft information' which received more recognition in China (Lee and Lee, 2012; Chen and Han, 2012). Platforms with a good reputation suggest trust has been established between the platform and investors; therefore, platform reputation is a kind of institution-based trust. Institution-based trust is especially suitable for P2P online lending where investors predominantly lend money to totally unknown and innominate borrowers under the circumstance that the platform (third party) provides the institutional context (Pavlou and Gefen, 2004).

Driven by new digital technology, P2P online lending platforms provide an alternative to traditional banking by bring together non-institutional borrowers and lenders (most are individuals or small business owners), while platforms act as information intermediaries. The innovation and popularity of P2P online lending leads to an efficient way of directly matching the supply and demand from small and medium sized borrowers and lenders (investors) to enable them to extend credit at lower rates compared to bank charges (Wei, 2015).

Although the innovative lending channel can expand the boundary of lending and reduce the cost of financial transactions, the information asymmetry between the two parties cannot be eased, but extended. This is because in the traditional lending market, investors can make investment decisions relying on the information disclosed by the company and the information required is regulated by the stock market or other regulations (Fishman and Hagerty, 1989). However, due to imperfect information disclosure mechanisms (e.g. borrowers' credit rating) and a lack of regulations in the P2P lending market, P2P investors mainly depend on the information disclosed by the platform about borrowers. If borrowers' moral hazard emerges (i.e. overdue loans and bad debts), investors will lose money. If many defaults occur, the platform will not continue to operate (Yang, 2016).

The moral hazard of P2P lending platforms is mainly caused by two reasons. Firstly, platforms (the agent) and investors (the principal) do not share the same objective/utility function. As shown in Figure 2, investors' interest is to maximise returns from investments, and therefore they care more about the return rate which is dependent on the credit status of borrowers. However, due to information asymmetry, anonymity and invisibility of online lending, investors can only acquire borrowers' information and credit scores disclosed selectively by lending platforms. Contrarily, the interest of lending platforms is to maximise commission fees/charges. If they set strict standards in selecting borrowers only with higher credit scores, their fees and charges would drop as a result that some borrowers would be removed. In such a case, lending platforms would have an intrinsic preference for maximizing income at the expense of investors – another kind of moral hazard from platforms.

Insert Figure 2 about here

Secondly, online lending currently does not have a mechanism to effectively monitor and control the behaviour of platforms. This mechanism exists in traditional lending through deposit contracts which can reduce the probability of moral hazard caused by information asymmetry (Campbell and Kracaw, 1980; Diamond, 1984). In other words, due to information asymmetry, investors are unable to restrain the behaviour of P2P platforms in faithfully releasing and evaluating the borrower's credit information. Therefore, investors face the moral hazard of P2P platforms who are agent regulators – the risk has become the largest risk in Chinese P2P lending (Wu, 2015) in recent years.

Due to the lack of an effective monitoring mechanism on P2P platforms, investors hardly evaluate their investment risks. They refer to peers' evaluation through the Internet on the reputation of the platform (e.g. lending volume, comments etc.). In other words, investors' choices put pressure on platforms in improving governance to reduce moral hazard. Therefore, it seems that we can suggest through investors' investment choices, platform reputation can play a governance role to prevent moral hazard of the platform. However, this suggestion implies a condition, i.e. the platform only acts as the intermediary between lenders and borrowers; but in fact, P2P platforms also have a credit enhancing function beside its intermediary role.

The most common credit enhancing method includes setting up risk reserves and capital. For example, the well-known UK P2P platform RateSetter has established a 'Provision Fund' to provide 'a buffer against any poorly performing loans. The Provision Fund covers fully or partially borrowers' default payments, and/or loss caused by the RateSetter platform itself (Terekhova, 2017). Provisional funds are also used by some Chinese P2P platforms as the prime credit enhancing method. Another credit enhancing method includes cooperating with third parties for guarantees (i.e. escrow services). For instance, in the UK, P2P platform 'Lending Works' provides 'Insurance backed lending' insured by external insurance companies. In China, 'Paipai Dai' (拍拍贷) and 'Yiren Dai' (宜人贷) also work with other third parties to provide lending insurance to reduce lenders' investment risk. As such, platform capital and credit enhancing information can increase platform reputation and lending transactions. In this case, to avoid the influence of platform credit enhancing information on the test results, it is necessary to control platform credit enhancing information when examining the effect of platform reputation. Thus, we propose Hypothesis 1 as follows:

Hypothesis 1: Controlling credit enhancing factors, platform Reputation will significantly affect the investment choices of investors.

The fundamental reason why the above credit enhancing information can influence investors' investment choice is because such information can increase investors' trust on the platform (Chen and Lin, 2014). On the Internet, trust between people is difficult to maintain through personality and interpersonal relationships, and thus institution-based trust becomes so important for Internet transactions (Pavlou and Gefen, 2004). Institution-based trust refers to the trust that is based on the mechanism designed to make investors feel safe (Zucker, 1986), including situational norms and structural guarantees (provisional fund and insurance through third party guarantees are two components) (Mcknight et al., 1998). Institutional-based trust is a fundamental factor for the platform reputation in Chinese P2P online lending (Gao and Zhao, 2017). We thus propose the second hypothesis with two sub-hypotheses expressed below:

Hypothesis 2a: Platform credit enhancing information will significantly affect the Reputation of the platform.

Hypothesis 2b: As a mediating variable, Reputation of the platform affect investors' investment choice through credit enhancing information.

4. Methodology

(1) Measurements and model building

Sample

The data was collected from the main P2P lending platform portals mentioned based on the availability of research variables. The original data was carefully scrutinised in dealing with exceptional and omitted values. The final sample includes 478 (295 healthy and 183 unhealthy) online P2P lending platforms and the data covers the periods from 1st June to 31st December 2017.

Table 1 defines research variables used in the study.

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Dependent variable (lnVolume)

From the game analysis shown earlier, it is understood that the impact of reputation is reflected by investors' investment choices and changes in the trading scale of the platform. As such, to test the effect of reputation, the trading volume of the platform is used as the predictor variable. Platform volume refers to the cumulative volume of each platform from June 1 to December 31, 2017. Logarithms were used to reduce the heteroscedasticity of data.

Prime independent variable – Calculating platform reputation (Reputation)

The '*Reputation*' of the 478 online lending platforms was calculated using a beta function calculator based on the trust model by Xiong and Liu (2004). Assuming that Beta probability density function is a continuous function composed of parameter α and parameter β, the Beta distribution f $(p|\alpha, \beta)$ may be expressed in the following equations:

$$f(p|\alpha,\beta)=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}p^{\alpha-1}(1-p)^{\beta-1},\quad where\ \ 0\le p\le 1,\ \alpha>0,\ \beta>0 \quad (1)$$

Expected Beta distribution E(p):

$$\mathrm{E}(p)=\alpha/\alpha+\beta \qquad (2)$$

Investors' reviews of online lending platforms are divided into positive reviews (r) and negative reviews (s). Assume that positive reviews may increase the reputation of online lending platforms, and negative reviews may decrease the reputation of online lending platforms. r_i and s_i are the number of positive reviews and negative reviews received by an online lending platform in the i^{th} month. R and S respectively refer to the positive reviews and negative reviews received by the platform during a period of time n ($R=\sum_i^n r_i$, $S=\sum_i^n s_i$).

According to Eq. (1), the following equation may be created:

$$\varphi(p|R,S)=\frac{\Gamma(R+S)}{\Gamma(R_i)\Gamma(S_i)}p^{R-1}(1-p)^{S-1}\qquad 0\le p\le 1,\ R>0,\ S>0 \qquad (3)$$

$\varphi(p|R,S)\varphi(p|R,S)$ may reflect the reputation of the platform. According to Eq. (2), the reputation value of the platform can be calculated through the following equation:

$$\mathrm{E}\big(\varphi(p|R,S)\big)=R/(R+S) \qquad (4)$$

$\mathrm{E}\big(\varphi(p|R,S)\big)$ is the reputation value calculated based on investors' reviews on a platform during a time period (n).

However, reputation value obtained through Eq. (4) has two problems. First, Eq. (4) assumes that both negative reviews and positive reviews have the same effects on platform reputation; while according to Park and Lee (2009) and Yang and Mai (2010), negative reviews have greater effects than positive reviews. Second, Eq. (4) fails to consider the fact that reviewers normally pay more attention to the latest reviews than the earlier reviews, i.e. earlier reviews would have less influence on reputation (Wen and Ye, 2014). Therefore, Eq. (4) should be revised as follows:

Assume that $\mathrm{R} = \delta \cdot \mathrm{S}$, and $\delta > 1$; negative reviews are given more weight.

$\mathrm{R} = \sum_i^n r_i \, \lambda^{n-i}, \; S = \sum_i^n s_i \, \lambda^{n-i}, 0 \leq \lambda \leq 1$; the weight of time is set.

The revised Eq. (4) reflects how reviews given at different moments affect reputation differently and was used to calculate the average reputation value of the 478 sample platforms.

Furthermore, to verify the reliability of platform reputation built, we also compared the rankings between our '*Reputation*' calculation and the one calculated by WDZJ in 2017 on 100 P2P platforms and found 81.77% of similarity which proved our calculation result significantly agreed with that produced by the reputable platform. The gap might be caused by the different components and numbers of platforms included between the two calculation systems, however our sample numbers (478) is significantly larger than the counterpart from WDZJ (100). This feature gives our study some merits.

Credit enhancing independent variables

There are generally two kinds of factors affecting platform credit conditions: platform registered capital funds and capital guarantee methods used by platforms. Loureiro and Gonzalez (2015) stated P2P lending can be used as a tool in allaying financial exclusion. Moreover, P2P platforms use their own funds and operations to gradually build reputation as collateral. As such, P2P platforms not only smooth credit and liquidity conversion, but also build credit (Li et al., 2016). In the presence of the information asymmetry problem, P2P platforms need to use a variety of methods to safeguard investors' money, e.g. provisional funds, mortgages on borrower's assets, financing or non-financing firm guarantees and joint liabilities by small loan companies. The more guarantee methods used by platforms, the higher the degree of safeguard for investors. We thus use types of capital guarantee methods as the measurement of *Guarantee* variable.

In China, apart from platform registered capital funds and capital guarantee methods, other factors of so-called *social capital* (soft information) can also influence the P2P lending platforms reducing the risk of adverse selection (Lin et al., 2013) and providing trust (Rieh, 2002). Chinese P2P investors rely more on this kind of soft information to make investment decisions (Chen and Han, 2012). The social capital generates mainly from the characteristics of P2P platforms, such as ownership and geographical locations.

The ownership of Chinese P2P platforms comprises of four types (see Table 2), that is (1) bank-involved, (2) publicly listed, (3) state-owned, and (4) private platforms. Bank-involved platforms are invested by commercial banks, which are well-funded with ample liquidity and qualification of getting access into China’s Central Bank Credit Reporting Database for obtaining borrower credit conditions to ease the information asymmetry problem. As such, they are the most attractive platforms for investors. Publicly listed platforms are established by listed companies to diversify businesses upstream and downstream of the industry chain. They are less popular compared to bank-involved platforms. State-owned platforms are held by state-owned companies and are implicitly endorsed by the state; however, the volume of lending transactions and participants are quite low because of the cautious nature of government policy. The largest number of P2P platforms is privately invested with the characteristics of early entry, low entrance threshold, high yield and risk. As a result, in terms of average volume of lending private platforms are at the lowest position (though they entered the market earlier than the other types). The unhealthiest platforms are amongst this kind. It is obvious from Table 2, there are apparent attribute differences of P2P platforms in China.

Insert Table 2 here

Another feature of social capital relates to geographical location of the platforms. The People's Congress of China classified provinces and municipalities into eastern, central and western regions based on per capita and gross domestic product (GDP). By the end of 2017, the eastern region consists of 11 coastal provinces representing a highly developed region, there are 8 provinces in the central region representing mid-level development, and 12 in the western region representing a less developed area. The development levels in different regions generally represent the levels of credit and social trust, with the eastern region having the highest, and the western region having the lowest (Zhang and Ke, 2002).

Analytical model building

Two models are set up to test the direct and indirect effects of reputation:

$$lnVolume = \gamma_0 + \gamma_1 Reputation + \gamma_2 Interest + \gamma_3 Month + \varepsilon \qquad (1)$$

$$lnVolume = \delta_0 + \sum_{i=1}^{t} \delta_i X_i + \theta \qquad (2)$$

In model (1), *lnVolume* is a log of the accumulated value of loans of the sample platforms from 01/06/17 to 31/12/17. *Reputation* represents the investor evaluation on platforms; *Interest* and *Month* are control variables. ε is error correction term. In model (2), X_i represents all explanatory and control variables explained in Table 3 including *Reputation, Type, Address, lnCapital, Guarantee, Month and Interest*. θ is error correction term.

(2) Descriptive statistics and correlation analysis

Descriptive statistics analysis

The variables' statistic description is summarised in Table 3.

Table 3 is around here

As shown in Table 3, the mean of *Reputation* of the 478 P2P platforms is close to 0.5, but the difference between the maximum and minimum values is significant, with the highest value reaching almost 1.0 and the lowest value just around 0.0005. This suggests the quality range of the sample P2P platforms represented by *Reputation* is larger. The mean of *Interest* is 12.79% with the highest and lowest value between 32% and 4.4%, suggesting the income of platforms is also dispersed. The *Month* represents the length of P2P loan ranging from 0.5 months to 43 months, with a mean of 4.6 months. With regards to loan volume (*lnVolume*), the average amount of loan value by sample platforms is 103,600 yuan (RMB), the maximum is 171,300 yuan, and the minimum is 38,500 yuan, with an average of 103,600 yuan. The average registered capital of the platforms is 82,900 yuan, with the maximum of 126,100 yuan and the minimum of 50,100 yuan. Regarding the types of guarantee approaches adopted by these platforms, the highest is 7 while the lowest is 0 suggesting these platforms do not have any measures and approaches to protect lenders. The average number of guarantee methods is just 1.58 (a very low reading). In terms of locations (*Address*) of the sample P2P platforms, 76% are located in the developed Eastern region while only 8.6% are in the less developed Western region, others are in the Central region. Regarding the types of platforms, 80% are privately owned, 8.4% are publicly listed while bank-involved platforms only account for 0.4% (equals 2 platforms), proving the majority of P2P platforms are informal lending providers.

Correlation analysis

lnVolume (dependent variable) and other variables were analysed using Spearman's rank correlation coefficient. As Table 4 indicates, *Reputation* is positively correlated with *lnVolume* and *Guarantee* at 1% statistically significant level. The same relationship was observed between *lnVolume* and *lnCapital*, *Month*, *Address1* (eastern), *Type 2* (bank involved), and *Type* 3 (publicly listed). In contrast, *Reputation* is negatively correlated with *Interest* and *Type 1* (private) at 1% statistically significant level. Similarly, *lnVolume* are negatively and statistically significant correlated with *Interest* and *Type 1* (private) at 1% level. The results suggest that P2P loan interest rates are not the main attracting factor for investors while platform reputation and other factors such as platform ownership and location also play important parts in their investment decision.

Insert Table 4 around here

5. Empirical findings

(1) Effects of platform reputation

Direct effects

Median regression, OLS regression, and random effect OLS regression are used to test the direct and indirect effects of *Reputation* on *lnVolume* (Jayaraman and Milbourn, 2012). Firstly, to test direct effects of *Reputation* on *lnVolume* in model (1), we control other variables which might influence *Reputation* indirectly including *lnCaptial*, *Guarantee*, *Type*, *Add*ress and the results are listed in columns 1, 2, and 3 of Table 5. Secondly, we test all variables in model (2) respectively and the results are listed in columns 4, 5 and 6 of Table 5 correspondingly.

Insert Table 5 around here

In columns 4, 5 and 6 of Table 5, *lnCaptial* (registered capital), *Type 2* (bank-involved) and *Address 1* (eastern region platforms) are strongly statistically significant which indicate they also significantly influence *Reputation* on *lnVolume*. This proves that when assessing direct effects of *Reputation* on *lnVolume* (Hypothesis 1), credit enhancing variables should be controlled. Columns 1, 2 and 3 of Table 5 indicate that *Reputation* has significant effects on *lnVolume* reaching statistical significance at 1% after controlling other credit enhancing factors. The results in columns 1, 2 and 3 further verifies Hypothesis 1.

Indirect effects (mediate effects)

According to Wen and Ye (2014), in order to examine whether *Reputation* has mediated on credit enhancing variables, three equations need to be established first:

$$\mathrm{lnVolume} = \mathrm{P} * \mathrm{Credit} + \sum_{i=1}^{t} \delta_i C_i + e_1 \qquad (5)$$

$$\mathrm{Reputation} = \mathrm{a} * \mathrm{Credit} + \sum_{i=1}^{t} \delta_i C_i + e_2 \qquad (6)$$

$$\mathrm{lnVolume} = \mathrm{P}' * \mathrm{Credit} + \mathrm{b} * \mathrm{Reputation} + \sum_{i=1}^{t} \delta_i C_i + e_3 \qquad (7)$$

Credit represents Credit-enhancing variables including *Address1*, *Address2*, *Type1*, *Type2*, *Type3*, *lnCapital* and *Guarantee*; $\sum_{i=1}^{t} \delta_i C_i$ are control variables (*Interest* and *Month)*; *P, P', a, and b* are coefficients, e_1, e_2, e_3 are error correction terms.

First step is to test equation (5): if *Credit* and *lnVolume* are not statistically significantly correlated, then the test of mediate effects should be abundant. It suggests that there is no mediate effect. If *Credit* is significantly correlated with *lnVolume*, it should be verified that *Reputation* is a mediate variable between the credit-enhancing variables and *lnVolume*.

Second step is to test coefficients *a* and *b* in equations (6) and (7): if *a* and *b* are significantly correlated, the coefficient *P'* in equation (7) needs to be further tested. If *P'* is not significant, it proves the mediate effects are fully disseminated by *Reputation*; if significant, it would suggest that the mediate effects are partially disseminated by *Reputation*. If either *a* or *b* is significant, the mediate effects can be further tested using the Sobel test (Sobel, 1982).

As such, testing the mediate effects is required to establish another two regression models:

$$lnVolume = \beta_0 + \beta_1 Adress1 + \beta_2 Adress2 + \beta_3 Type1 + \beta_4 Type2 + \beta_5 Type3 + \beta_6 lnCapital + \beta_7 Guarantee + \beta_8 Interest + \beta_9 Month + e_1 \qquad (3)$$

$$Reputation = \beta_0 + \beta_1 Adress1 + \beta_2 Adress2 + \beta_3 Type1 + \beta_4 Type2 + \beta_5 Type3 + \beta_6 lnCapital + \beta_7 Guarantee + \beta_8 Interest + \beta_9 Month + e_2 \qquad (4)$$

Models (3) and (4) are mainly used to test the impact of credit enhancing information on *lnVolume* and *Reputation* respectively, though control variables are included. The results from median regression, OLS regression, and random effect OLS regression are reported in columns 1, 2, and 3 (*lnVolume*) and 4, 5 and 6 (*Reputation*) of Table 6 accordingly.

Insert Table 6 around here

From columns (1), (2) and (3) of Table 6, one can see credit enhancing variables *lnCapital*, *Type1*, *Type 2* and *Address 1* have positive and significant effects on *lnVolume*. This suggests *Reputation* plays mediate roles on these variables but not on *Type3, Address* 2 and *Guarantee* (recording them "no" in the final column of Table 6). From columns (4), (5) and (6), of Table 6 we observed credit enhancing variables (*lnCapital, Type1, Address 1, Guarantee) and control variables* (*Interest, Month)* are significant. The results support Hypothesis 2a.

Furthermore, the significance in columns (4), (5), and (6) of Table 6 for credit enhancing variables *(lnCapital, Type1, Adress1)* suggests coefficient *a* in equation (6) is significant. Similarly, the significance of coefficient *b* in equation (7) can be seen from the columns (4), (5) and (6) in Table 5. If we count the numbers of variable significance in the columns (4), (5) and (6) of Tables 5 and 6 respectively and record them in the final column of Table 6 (e.g. both *a* and *b* are significant, recording as 2; either *a* or *b* is significant, recording as 1), we can see *lnCapital, Type1, Adress1* have both *a* and *b* significant (counting 2). Taking the 3 variables back to further observe the columns (4), (5) and (6) in Table 5, we found *lnCapital*, and *Adress1* are statistically significant but not for *Type1*.

The results suggest that *Reputation* has partial mediate effects on *lnCapital*, and *Adress1* while full mediate effect on *Type1*.

The final column of Table 6 shows that in the *Reputation*'s direct (Table 5) and indirect (Table 6) effect regression analyses, *Type 2* only shows one significant (counting 1), therefore, *Reputation*'s mediating effect on this variable requires to be further verified by the Sobel test. In the Sobel test, platform CEOs' education level (*edu*) was added as an instrumental variable. The test results are listed in Table 7.

Insert Table 7 around here

As shown in Table 7, *Reputation* has no significant mediating effect on *Type 2* (only 3.023%).

From the analyses in Tables 5, 6 and 7, we can conclude that platform reputations (*Reputation*) have partial mediate effects on platform registered capital (*lnCapital*), platforms located in the eastern area (*Address 1*), full mediate effects on private platforms (*Type 1*). Platform reputations (*Reputation*) have no obvious mediate effects on bank-involved platforms (*Type 2*), publicly listed platforms (*Type 3*), platforms located in the western region (*Address 2*), and platform guarantee methods (*Guarantee*). Thus, Hypothesis 2b has been partially verified, that is, platform reputations have mediating effects on some credit enhancing variables.

(2) Further evidence and robust test

Further test by adding instrument variables

Considering endogenous problems among independent variables, we set up the following test using two instrumental variables to confirm the results shown above. The first instrumental variable is *Edu* (CEO's qualification). According to Hinojosa (2002), the CEO's educational level is crucial for the development/reputation of the platform as it can generally reflect the capability of the CEO (Spence, 1974). A dummy variable is used, with 0 representing CEO qualification at first degree or below, and 1 representing Master or above. The second instrumental variable is *Join,* with 1 representing that the platform is a member of the Internet Banking Association (IBA), while 0 is for not joining the IBA. This is because according to the membership rule of IBA established in 2016, only platforms which are qualified with 3 criteria: (1) registered with the industrial authorities, (2) no serious violations in the last three years, and (3) no bad record from the management team, can apply for membership of the IBA. As such, investors treat IBA membership as representative of the platform's self-discipline reputation and good governance, in other words, having platform reputation.

Using *Join* and *edu* as instrumental variables, model (5) is established as follows：

$$Reputation = \alpha_0 + \alpha_1 Join + \alpha_2 edu + \alpha_3 Interest + \alpha_4 Month + \alpha_5 lnCapital + \alpha_6 Adress1 + \alpha_7 Adress2 + \alpha_8 Type1 + \alpha_9 Type2 + \alpha_{10} Type3 + \alpha_{11} Guarantee + \varepsilon_2 \quad (5)$$

After using OLS estimation model (5), a fitting value (prPep) was formed. Using *join* and *edu* as instrumental variables and *lnVolume* as dependent variable, we run regression again and the results are listed in Table 8.

Insert Table 8 around here

The regression results in Table 8 show, in the first stage of the regression *Reputation* is significantly positively related to the two added instrumental variables (*join* and *edu*), which suggests IBA and CEO's qualifications are attributed to platform reputation. The second stage of the three OLS regression results show that after the first stage regression fitting, the obtained prRep and platform trading volume are positively and significantly correlated. This regression result is the same with that in the columns (4), (5) and (6) of Table 5. The results indicate that after controlling endogenous variables, the results stay the same. Therefore, the evidence supporting the argument of this paper is strengthened.

Robust test

To further confirm the results, a robust test was run by replacing *lnVolume* by the duration of platforms (*lnTime*), and model (6) is established as follows：

$$lnTime = \alpha_0 + \alpha_1 Reputation + \alpha_2 Interest + \alpha_3 Month + \alpha_4 lnCapital + \alpha_5 \mathrm{Adress1} + \alpha_6 Adress2 + \alpha_7 Type1 + \alpha_8 Type2 + \alpha_9 Type3 + \alpha_{10} G\mathrm{uarantee} + \varepsilon \quad (6)$$

The results from median regression, OLS regression, and random effect OLS regression of model (6) are reported in columns 1, 2, and 3 of Table 9 accordingly.

Insert Table 9 around here

In Table 9, median regression is not significant, both OLS regression and random effects OLS have shown that *Reputation* and platform duration have a positive significant correlation. The results robustly confirm that platform reputation strongly influences the development of P2P platforms.

6. Conclusion and implications

The recent Chinese P2P platform financial explosion turmoil highlights the importance of platform reputation. In this highly competitive industry, platforms with a good reputation can survive and sustain whereas those having a bad reputation could be eliminated. If financial explosion reaches a serious level, it will cause public panic and society turbulence. As such, examining how P2P platform reputation can positively or negatively affect lenders' lending choices is an urgent and meaningful matter. This study has addressed this less researched area by examining what factors can influence P2P platform reputation and in what ways. Using data collected from 478 Chinese P2P platforms (about a quarter of the population) and rigorous statistical analysis, we tested platform reputation's direct and indirect factors in influencing investors' choices.

The results conclude these findings (1): primarily, platform reputation can directly and positively influence investors' investment choices (measured by lending transaction volume); (2) indirectly and positively, platform reputation affect investors' investment choices through some platform credit enhancing information (i.e. platform registered capital, platforms located in the eastern region, platforms with bank involved lending and guarantee methods). In other words, platform reputation negatively influences lending transaction volume through other credit enhancing information, such as platforms located in other regions, other platform types, interest and length of loans. Our findings also reveal (3) the quality of P2P platforms in China is wide ranging and many P2P platforms are poor quality; (4) the types of guarantee methods used by Chinese P2P platforms are less than two (a mean of 1.58); (5) imbalanced platform locations with three quarters (75%) located in the developed eastern region; (6) 80% are privately owned platforms (as expected); however their reputation is much lower than bank-involved platforms; and (7) platform reputation is negatively correlated with interest which suggests that P2P loan interest rates are not the main attracting factor for investors while other factors such as platform ownership and location are more important in investment decision making.

An important contribution of this paper to literature is evidence provided that platform credit enhancing information provides platform reputation information onto investors (i.e. playing a mediate role). To the best of our knowledge, this study is the first research examining the role of credit enhancing information between P2P lending platforms and their investors. Our findings have several important policy implications. Firstly, considering the fact there are many low-quality P2P platforms, Chinese central and local governments and industry associations (e.g. Internet Banking Association - IBA) need to speedily establish relevant regulations, policies and industrial standards to eliminate these platforms in order to formalise, stabilise and improve the prosperity of the P2P lending market. In other words, new regulations/policies should protect effective platforms with good reputation. Secondly, although it is reasonable that the majority of P2P platforms are located in the developed eastern region, this imbalance in geographic distribution is worthy to note and preferential policies should be established to support less developed regions (especially the western region). Thirdly, the majority (80%) of P2P platforms are privately owned and their reputation is significantly lower than bank-involved platforms. This is a special Chinese characteristic originating from the centrally planned economy where people regard state-owned bank involved platforms much safer than privately owned ones. However, in the P2P lending market, it is impossible that state-owned bank involved platforms can replace the latter. As such, regulations and policies to support and protect private platforms to help improve their reputation should be a long-term strategy for the Chinese government and industrial regulators. Fourthly, our findings reveal that Chinese P2P platforms use few guarantee methods, and this puts investors at greater risk. New industrial standards and regulations should also deal with this to protect the interest of lenders to minimise the turbulence of this market mentioned in the introduction.

As with other studies, this research has several limitations. We highlight them in two aspects: one relates to sample size and another relates to proxy measurement. In terms of sample size, our sample contains 478 platforms which only counts for about one fourth of the platform population in China. This is because of the data availability from the popular platform portals in relation to variables assigned with our research objective. However, our sample made a balance between large and small platforms, as well as healthy and unhealthy platforms. With this unique feature, the sample's representativeness of the population is good, and the findings consequently have explanation powers. With regards to the proxy measurement, the study uses platform trading volume as the proxy of platform reputation rather than investors direct feedback/experience. Although this measurement is indirect, it is reasonable when feedback/experience is absent or incomplete that platform transaction value is one of the most important performance measurements used by platforms. Future research should also consider how to collect data to measure the roles of platform reputation in mitigating moral hazard of P2P platforms. In this paper we are only able to theoretically prove this role.

Acknowledgment

We deeply appreciate the anonymous reviewers for the highly constructive comments and Professor Hooman Estelami (the editor) for his excellent guidance. We are grateful for financial support from The National Social Science Fund of China 国家社科基金 (Project: 15BJY173) and Humanities and social sciences fund of the Ministry of Education 教育部人文社科基金 (Project: 13YJA790098).

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Tables and Figures

Table 1 Definition of Research Variables

Variables	Definition	Measurement
Dependent variable		
lnVolume	Platform loan value	Logarithm of the accumulated value of loans granted via sample platforms
Prime independent variable		
Reputation	Platform reputation	Calculated using the Beta function
Credit-enhancing independent variables		
lnCapital	Platform registered capital	Logarithm of platform registered capital
Guarantee	Capital guarantee methods used by platforms	Numbers of types of capital guarantee methods
Type	Background of the platforms	Using state-owned bank as benchmark, 3 dummy variables are defined as: Type 1 (privately owned platforms): 1 for yes and 0 for others; Type 2 (bank involved platforms): 1 for yes and 0 for others; Type 3 (publicly listed platforms): 1 for yes and 0 for others.

Address	Geographical distribution[1] of the platform (Central area, Eastern area and Western area). Central area as benchmark.	2 dummy variables are defined as: Address 1 (platforms located in Eastern area): 1 for yes and 0 for others; Address 2 (platforms located in Western area): 1 for yes and 0 for others.
Control variables		
Month	Average loan length	Average term (month) of online loans
Interest	Average annual loan interest rate	Average annual interest rate of online loans

Note: (1) '*Guarantee'* is measured by the types (diversity) of capital guarantee methods as the more diversified guarantee methods used, the safer investors' capital would be. These methods include loan loss provisioning, third-party guarantee, mortgage lending, platforms paying overdue loans, and small loan companies reviewing loans and assuming joint and several liabilities. (2) The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong and Hainan. The central region includes Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan. The western region includes Chongqing, Inner Mongolia, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.

[1] The geographical distribution was initially set by the People's Congress of China in 1986, measured by GDP per capita. As to 2017, there are 12 eastern coastal provinces/municipalities/autonomous regions are classified as developed, 12 in the west are less developed and 8 in central are between the East and West in terms of economic development.

Table 2 Ownership of Chinese P2P platforms

Type	Total trading volumn (100 million RMB))	Platform (No.)	Average trading volumn (Trading volumn/per platform)	Average monthly lenders 10,000/ per platform	Average monthly borrowers 10,000RMB/per platform
Bank involved	164.92	6	27.48	5.375	5.82
Publicly listed	618.03	115	5.37	1.054	1.138
State-owned	205.09	212	0.967	0.190	0.205
Privately owned	900.26	1486	0.606	0.119	0.128

Source: https://www.wdzj.com/ (网贷之家)

Table 3 Descriptive Statistics of Variables

Variable	Sample	Mean	SD	Minimum	Maximum
Reputation	478	0.4978891	0.3093119	0.0005459	0.999851
Interest	478	12.79919	3.956787	4.388333	32
Month	478	4.63849	4.657924	0.5116667	43.45667
lnVolume	478	10.36307	1.938305	3.849509	17.13208
lnCapital	478	8.292295	1.030755	5.010635	12.61154
Guarantee	478	1.582439	1.07353	0	7
Adress1	478	0.7635983	0.4253168	0	1
Adress2	478	0.0857741	0.2803235	0	1
Type1	478	0.8012552	0.3994736	0	1
Type2	478	0.0041841	0.0646168	0	1
Type3	478	0.083682	0.2772004	0	1

Table 4 Correlation Analysis of Variables

	lnVolume	*Reputation*	*lnCapital*	*Type1*	*Type2*	*Type3*	*Adress1*	*Adress2*	*Interest*	*Month*	*Guarantee*
lnVolume	1										
Reputation	0.1349*	1									
lnCapital	0.3469*	0.0331	1								
Type1	-0.2427*	-0.1323*	-0.2274*	1							
Type2	0.1038*	-0.0272	0.1050*	-0.1302*	1						
Type3	0.2175*	0.1130*	0.1696*	-0.6068*	-0.0196	1					
Adress1	0.3416*	0.0140	0.2390*	-0.0673	0.0361	0.1148*	1				
Adress2	-0.1561*	-0.0466	-0.1612*	0.0215	-0.0199	-0.0386	-0.5505*	1			
Interest	-0.4128*	-0.2332*	-0.3097*	0.4076*	-0.1097*	-0.2385*	-0.3244*	0.1222*	1		
Month	0.2445*	0.1452*	0.2207*	-0.1428*	0.1052*	0.1559*	0.0651	-0.0757	-0.1326*	1	
Guarantee	0.0770	0.1633*	0.0267	-0.0847	0.0285	0.0254	-0.0112	0.0566	0.1469*	0.0941*	1

Note: '*', '**', '***' represent statistically significant at 10%, 5%, 1% respectively.

Table 5 Regression Test of Direct Effect of Platform Reputation

	lnVolume			*lnVolume*		
	(1)	(2)	(3)	(4)	(5)	(6)
Reputation	3.730***	3.952***	3.9798***	1.943***	2.448	2.473***
	(0.590)	(0.544)	(0.5446)	(0.630)	(0.556)	(0.557)
Interest	-0.323***	-0.305***	-0.3067***	-0.157***	-0.178***	-0.180***
	(0.0419)	(0.0387)	(0.03866)	(0.0456)	(0.0402)	(0.0402)
Month	0.100***	0.114***	0.1145***	0.0871***	0.0807***	0.0811***
	(0.0281)	(0.0259)	(0.2589)	(0.0281)	(0.0248)	(0.0248)
lnCapital				0.347***	0.309***	0.308***
				(0.0910)	(0.0803)	(0.0803)
Type1				-0.213	-0.186	-0.187
				(0.287)	(0.254)	(0.254)
Type2				4.330***	3.084**	3.087***
				(1.370)	(1.208)	(1.208)
Type3				0.499	0.445	0.455
				(0.399)	(0.352)	(0.352)
Adress1				0.986***	1.083***	1.077***
				(0.255)	(0.225)	(0.225)
Adress2				0.0820	0.129	0.128
				(0.371)	(0.327)	(0.327)
Guarantee				0.106	0.0829	0.0841
				(0.0832)	(0.0734)	(0.0735)
Constant	10.28***	9.967***	9.9572***	6.470***	6.708***	6.605***
	(0.167)	(0.154)	(0.1544)	(0.8540)	(0.734)	(0.741)
R-squared		0.166	0.1679		0.2828	0.2836
Pseudo R^2	0.0977			0.1673		
Observations	478	478	478	478	478	478

Note: '*', '**', '***' represent statistically significant at 10%, 5%, 1% respectively.

Table 6 Regression Test of Indirect Effect of Platform Reputation

	lnVolume			***Reputation***			**Number of significant**
	(1)	(2)	(3)	(4)	(5)	(6)	
Interest	-0.0432*	-0.0260	-0.0259	0.0693***	0.0623***	0.0623***	
	(0.0247)	(0.0208)	(0.0208)	(0.0019)	(0.0017)	(0.0017)	
Month	0.104***	0.0998***	0.100***	0.0091***	0.0079***	0.0074***	
	(0.0296)	(0.0249)	(0.249)	(0.0023)	(0.0020)	(0.0020)	
lnCapital	0.334***	0.356***	0.356***	0.0150**	0.0193***	0.0194***	2
	(0.0964)	(0.0811)	(0.0812)	(0.0076)	(0.0066)	(0.0066)	
Type1	-0.503*	-0.440*	-0.443*	-0.0784***	-0.104***	-0.103***	2
	(0.299)	(0.252)	(0.252)	(0.0237)	(0.0205)	(0.0205)	
Type2	4.362***	2.923**	2.294**	0.0579	-0.0657	-0.0658	1
	(1.462)	(1.231)	(1.232)	(0.116)	(0.100)	(0.100)	
Type3	0.458	0.477	0.478	0.0181	0.0090	0.0090	no
	(0.426)	(0.358)	(0.359)	(0.0337)	(0.0292)	(0.0292)	
Adress1	1.128***	1.251***	1.248***	0.0560***	0.0687***	0.0691***	2
	(0.268)	(0.226)	(0.226)	(0.0212)	(0.0184)	(0.0184)	
Adress2	0.114	0.213	0.213	0.0331	0.0343	0.0343	no
	(0.369)	(0.333)	(0.333)	(0.0313)	(0.0272)	(0.0272)	
Guarantee	0.128	0.109	0.110	0.00857	0.0105*	0.0104*	no
	(0.0887)	(0.0746)	(0.0747)	(0.0070)	(0.0061)	(0.0061)	
Constant	6.908***	6.477***	6.482***	-0.0823	-0.0493	-0.0498	
	(0.896)	(0.755)	(0.755)	(0.0709)	(0.0615)	(0.0615)	
R-squared		0.253	0.2533		0.805	0.8051	
Pseudo R^2	0.1525			0.6262			
Observations	478	478	478	478	478	478	

Note: '*', '**', '***' represent statistically significant at 10%, 5%, 1% respectively.

Table 7 Sobel test

	Type2			
	Coef	**Std Err**	**Z**	**P>|Z|**
sobel	0.000757	0.00126	0.603	0.546
Goodman-1(Aroian)	0.000757	0.00157	0.483	0.629
Goodman-2	0.000757	0.00083	0.908	0.364
a coefficient=	0.00484	0.00428	1.132	0.258
bcoefficient=	0.156	0.219	0.713	0.476
Indirect effect=	0.000757	0.00126	0.603	0.546
Direct effect=	0.0258	0.0205	1.259	0.208
Total effect=	0.025	0.0205	1.224	0.221
Proportion of total effect that is mediated				0.03023
Ratio of indirect to direct effect				-0.0293
Ratio of total to direct effect				0.971

Table 8 Regression Test by adding instrumental variables

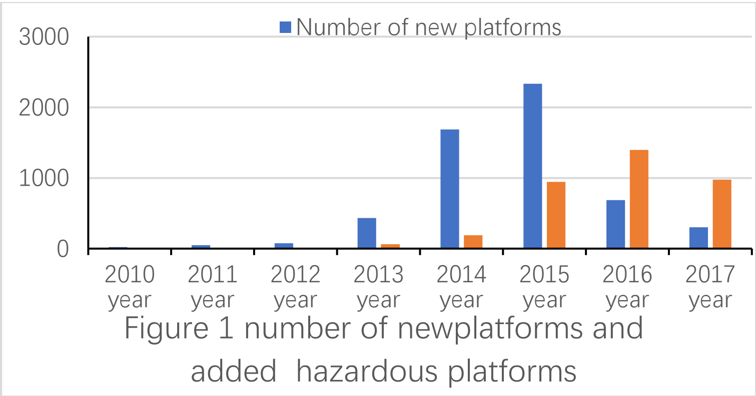
	1st stage	2nd stage		
	Reputation	***lnVolume***		
	(1)	(2)	(3)	(4)
edu	0.01750*			
	(0.0129)			
Join	0.0648***			
	(0.01562)			
prRep		14.34***	17.41***	17.42***
		(3.175)	(2.609)	(2.610)
Interest	0.0624***	-0.936***	-1.110***	-1.111***
	(0.0017)	(0.199)	(0.164)	(0.164)
Month	0.0058***	-0.0065	-0.0357	-0.0354
	(0.0020)	(0.0381)	(0.0313)	(0.0313)
lnCapital	0.0149**	0.0739	0.0195	0.0187
	(0.0066)	(0.113)	(0.0925)	(0.0926)
Type1	-0.0877***	1.064***	1.368***	1.365***
	(0.0205)	(0.441)	(0.362)	(0.363)
Type2	-0.0903	5.370***	4.066***	4.068***
	(0.0985)	(1.448)	(1.190)	(1.190)
Type3	0.0025	0.491	0.321	0.321
	(0.0287)	(0.418)	(0.344)	(0.344)
Adress1	0.058***	0.0872	0.0540	0.0503
	(0.0182)	(0.342)	(0.281)	(0.281)
Adress2	0.0308	-0.591	-0.385	-0.386
	(0.0267)	(0.403)	(0.331)	(0.331)
Guarantee	0.00682	-0.0098	-0.7414	-0.0731
	(0.00603)	(0.0930)	(0.0764)	(0.0765)
Constant	-0.0322	7.490***	7.335***	7.340***
	(0.0604)	(0.892)	(0.733)	(0.733)
R-squared	0.813		0.318	0.3184
Pseudo R2		0.1896		
Observations	478	478	478	478

Note: '*', '**', '***' represent statistically significant at 10%, 5%, 1% respectively.

Table 9 Robustness test

	lnTime		
	(1)	(2)	(3)
Reputation	0.0427	0.2243***	0.2249***
	(0.0724)	(0.0860)	-0.0861
Interest	-0.0043	0.0116	0.0113
	(0.0064)	(0.0076)	(0.0077)
Month	0.0202***	0.0217***	0.0218***
	(0.0047)	(0.0056)	(0.0056)
lnCapital	0.0008	0.0409	0.0405
	(0.0226)	(0.0269)	(0.0269)
Type1	0.0799	0.0601	0.0605
	(0.0718)	(0.0852)	(0.0852)
Type2	0.4160	0.5967	0.5956
	(0.3403)	(0.4039)	(0.4042)
Type3	0.11489	0.2353*	0.2354*
	(0.0985)	(0.1170)	(0.1170)
Adress1	0.0558	0.0448	0.0429
	(0.0639)	(0.0759)	(0.0759)
Adress2	0.0569	0.0345	0.0340
	(0.0916)	(0.1087)	(0.1088)
Guarantee	0.0313	0.0406*	0.0408*
	(0.0204)	(0.0243)	(0.0243)
Constant	3.1280***	2.4192***	2.4268***
	(0.2411)	(0.2860)	(0.2867)
Observations	478	478	478
R-squared		0.087	
Pseudo R2	0.0439		0.0367

Note: '*', '**', '***' represent statistically significant at 10%, 5%, 1% respectively.



Data sources: P2PEYE.com

Note: hazardous plateforms refer to the platforms with overdue loans and bad debts.

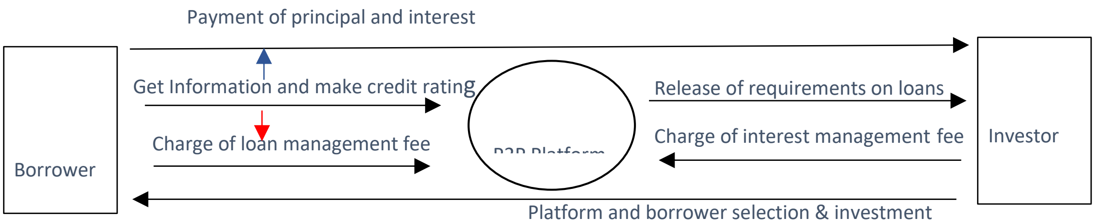


Figure 2 Parties Involved in P2P Lending and Their Relationships